Design and Development of k-stage architecture for breast cancer diagnosis using ResNet based network and XGBoost classifier

A Synopsis Submitted to Mandsaur University for Registration of Doctoral Programme

Jan 2020

Submitted by

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(MUPHD/2019/0327)

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CERTIFICATE

This is certified that the proposed Research work of the Synopsis of Ph. D thesis Entitled "**Design and development of k-stage architecture for breast cancer diagnosis using Resnet based network and XGBoost classifie**r" has not been done earlier by anybody in any University.

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ABSTRACT

It is essential to detect breast cancer at earlier stage because the survival rate of patient depends on the earlier diagnosis of breast cancer. There are two types of breast cancer one is benign and other is malignant. Benign is noncancerous but in some cases it may convert in to cancerous state, whereas malignant is cancerous. Timely diagnosis and treatment of cancer can only save the life of patient. For diagnosis of breast cancer there are different modern photography techniques which are classified as invasive and noninvasive. Ultrasound, X-ray, Computer aided Tomography, Magnetic Resonance Imaging are noninvasive techniques whereas histopathological imaging (Biopsy imaging) is an invasive technique. Researchers have identified different algorithms and investigation methods to examine images from different perspective. Machine learning, Deep learning, Artificial Intelligence are widely used for image classification. Manual inspection of these images by doctors and radiologists is a tedious task. Therefore a computer aided diagnosis system needs to be developed to identify the region of interests. By performing a rigorous literature review of 25 research papers taken from standard journals (Springer, Elsevier, ieee etc…) and conference papers, certain research gaps are identified and based on these research gaps, our research focuses on the design and development of a novel k-stage Resnet network and the XGBoost classifier model for early diagnosis of breast cancer. The designed network would be trained using a large amount of normal, benign and malignant images so that we can increase the accuracy of the computer aided-diagnosis system. The datasets will be collected through the different available breast cancer databases, and it will be analyzed using different tools such as Python, Tensor flow, Deep neural network and the k-stage Resnet network. The expected outcome of this research is early diagnosis of breast cancer with higher accuracy.

Keywords: *Deep learning, Machine learning, Artificial Intelligence, Resnet, XGBoost*

OUTLINE OF THE PROPOSED RESEARCH WORK

I. Title of the Research Work:

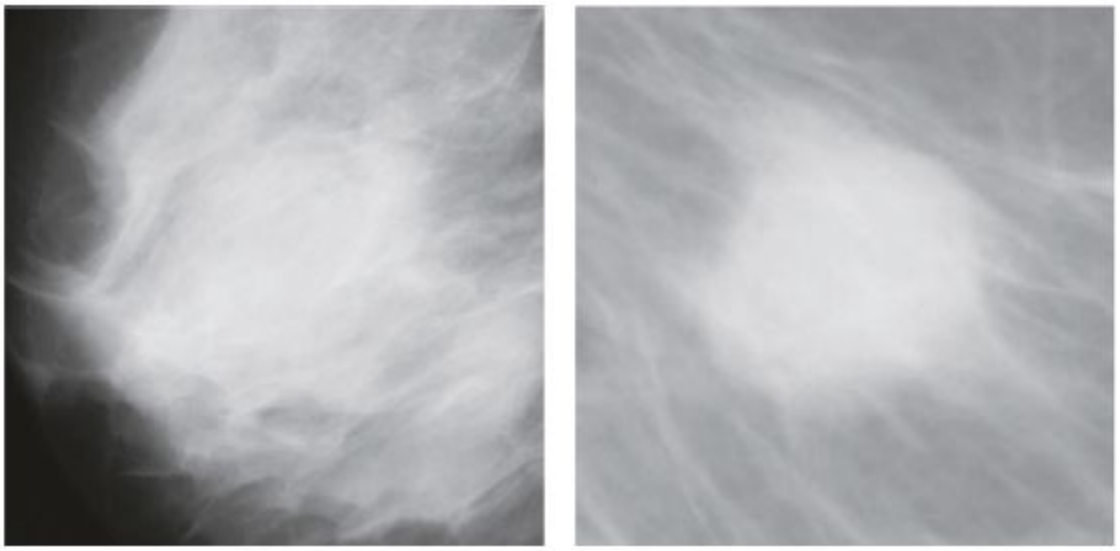
Design and Development of k-stage architecture for breast cancer diagnosis using ResNet based network and XGBoost classifier.

II. Importance/ Rationale of Proposed Investigation:

Across the globe after lung cancer, breast cancer is the second most deadly type of cancer. 2 billion cases of breast cancer were reported globally whereas 6,27000 deaths occurred in 2018. According to a study, the chances of cancerous patient survival depends upon the size of the tumor at the time of diagnosis, if the size of the tumor is less than 10mm the probability of survival of the patient is 98% whereas 70% of the cases are diagnosed when the size of tumor exceeds 30mm. During screening the tumor becomes evident when the size is at least 20mm. Therefore timely diagnosis of breast cancer is essential for early treatment.

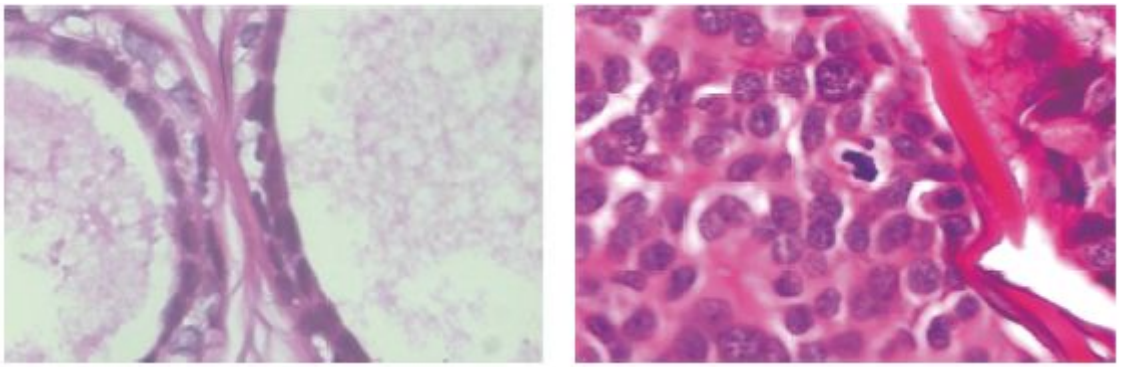
III. Scope of Proposed Investigation

Cancer is always a life-threatening disease. The lives of people can be saved only through proper treatment of cancer. Inside the body there is a regeneration process to maintain the cells. It is a natural mechanism of the body to sustain the steady growth and death rate of the cells, but every time this isn't the case. However an abnormal circumstance arises, when anomalous cells start developing. There are different types of cancer which can devise inside the human body, among them a serious health concern is breast cancer. Women are more at risk of breast cancer as compared to men due to the structure of the human body. The various factors for breast cancer are hereditary, age, breast density, fatness, drinking alcohol. Globally across the world today breast cancer is the leading cause of women's death. The current statistics reveal that in recent years the situation has become worse. It is basically classified into two types Benign (Non cancerous) and Malignant (Cancerous). The first and foremost step for the treatment of cancer is the identification of normal, benign and malignant tissues. Benign is non-life threatening as it is considered as non cancerous. But there is a probability that it could turn into a cancerous state, whereas malignant cancer begins from anomalous cell growth and it may quickly spread or attack surrounding tissues. For the diagnosis of benign and malignant tissues in the body imaging of the particular area of the body is identified and the doctor and physician target that area for diagnosis.



(a) (b)

Figure (a,b) show mammogram of noninvasive image



(c) (d)

Figure (c,d) are Histopathological invasive image

XGBoost stands for extreme gradient boosting. It is widely used in various systems and algorithmic optimizations. For processing sparse data it is a novel tree learning algorithm, theoretically justified weighted quantile sketch procedure enables handling instance weights in approximate tree learning. For rapid learning and easier model exploration parallel and distributed computing are used. It enables scientists to compute hundred millions of data samples on a desktop. Finally it helps in combining various techniques to develop an end-to-end system that can compute large amount of data with a very less quantity of cluster resources.

A Resnet is an artificial neural network which is developed from pyramidal cells in the cerebral cortex. The skip connections are utilized, or shortcuts are used to jump over some layers for this purpose. A double-or triple- layer skips are added which contain nonlinearities (ReLU) and batch normalization in between for implementation purpose. The HighwayNets are the models which are used to learn from the skip weights, and to represent them additional weight matrix are used. The DenseNets are the models which contains several parallel skips. In the context of residual neural networks, a non-residual network may be described as a plain network.

IV. Location:

a) Organization/Department where the work is to be done:

Mandsaur University, Mandsaur
Department of Computer Science & Engineering

b) Geographical Area of Investigation, if any: Global

V. Research gaps identified in the proposed field of investigation:

- The frequency domain image features are not considered while applying evolutionary algorithms.
- Most of the research work done deals with binary classification, further evolutionary techniques need to be applied to learn multi class mammographic densities.
- The Support vector machine algorithm gives the efficient results but we can further increase the accuracy percentage.
- The size of the data sets needs to be increased for mining the various diagnostic patterns.
- The training of deep CNNs is affected by the proportion of data sets in different classes i.e. between benign and malignant mass lesions, so training samples size need to be equal.

VI. Objective of the proposed study:

- Design a k stage architecture and train the network using large amount of images and then increase the accuracy of computer aided diagnosis system
- Implementation of breast cancer diagnosis system based on XG boost classifier which will focus on mass region and multi class mammographic densities which are not explored in previous researches.
- To increase the AUC of the existing 2 stage Resnet network.

VII. Review of Work done on the Subject:

1. **Shirazi F et al. (2016)** implemented a support vector machine (SVM) & Mixed Gravitational Search Algorithm (MGSA) together for feature reduction and grey level co-occurrence matrix (GLCM) to extract the features. The images are mammograms types and regions of interest (ROI) are extracted for reducing redundant complexity. The accuracy achieved by SVM is 86.00% while the accuracy achieved by MGSA-SVM is 93.1%.
2. **Taheri M et al. (2016)** implemented Support vector machine (SVM) & Harris corner detection together, the images are classified as normal and abnormal images. For reducing the redundancy and computational complexity the noise is removed from the images. In this study, automatic thresholding is used and based on the experimental result it can be said that this method is more accurate as compared to manual thresholding. The images are mammogram types. The achieved precision and recall rates are 96.80% and 92.5% respectively.
3. **Suzuki S et al. (2016)** developed a transfer learning strategy to solve the training problem DCNN (Deep convolutional neural network) for mass detection in mammographic CAD (computer aided diagnosis) application. A huge amount of natural images are firstly used for pre-training and then a relatively small number of mammographic images are used for transfer learning. They finally achieved 89.90% sensitivity.
4. **Qiu Y et al. (2016)** built and tested a novel model based on deep learning technology to predict the near term risk of breast cancer. Their CAD scheme enables them to adaptively search for and select the optimal features to compare the bilateral asymmetry of the breast or mammographic density related image features between the left and right mammograms for predicting the risk of breast cancer. The overall accuracy was 71.4%.
5. **Kooi T et al. (2016)** showed that a deep learning model in the form of a convolutional neural network trained on a large data set of mammographic lesions outperforms a state of the art system in CAD. Addition of location information and context can easily be added to the network and that several manually designed features in the form of common sense can give some small improvement. 44090 mammogram type images were used and the transfer learning method utilized using (VGG model).
6. **Jiao Z et al. (2016)** proposed a novel mammographic masses classification framework. Fine tuning operation is applied on trained deep CNN models to acquire the feature extraction network. Weighted similarity was calculated to decide labels of the uncertain set. Their experimental results demonstrated that the CNN model with adjustment for

certain data was effective even if the scale of a specific database was not large. They achieved 97% accuracy.

7. **Lashkari A E et al. (2016)** Compared supervised learning technique with unsupervised technique. Fuzzy c-means clustering technique was used as an unsupervised method and compared with AdaBoost supervised classifier. Fuzzy c-means clustering achieved 77% accuracy whereas AdaBoost technique achieved 88% accuracy. For the classification purpose 23 features were selected and best was determined using a selection algorithm.
8. **Raghavendra U et al. (2016)** used Gabor wavelet for feature extraction and locality sensitive discriminant analysis (LSDA) for data reduction. The reduced feature are ranked using their F-values and fed to decision Tree, Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA), k-nearest neighbor (k-NN), Naïve bayes classifier (NBC), probabilistic neural network (PNN), support vector machine (SVM), AdaBoost and Fuzzy sugeno (FSC) classifier. They evaluated 690 mammogram images and achieved mean accuracy, sensitivity, specificity of 98.69%, 99.34% and 98.26% respectively.

9. **Żejmo M et al. (2016)** presented automatic classification of tumors of breast using deep learning methodology based on fine needle cytology. Small patches of cytological images were selected and then processed. CNN is used to process the images. The resultant information provides the output whether the tumor is benign or malignant. They achieved 83% accuracy for best patch classification using GoogleNet model.
10. **Tajbakhsh N et al. (2016)** demonstrated that deeply fine-tuned CNNs are useful for medical image analysis. Their results showed that knowledge transfer from natural image to medical image is possible. For pulmonary embolism they achieved performance saturation after fine tuning the late fully connected layers, for colonoscopy frame classification they achieved highest performance through fine tuning the late and middle layers and for interface segmentation and polyp detection highest performance was achieved by fine tuning all layers in pre trained CNN.
11. **Asri H et al. (2016)** applied four main algorithms Support vector Machine (SVM), Naïve bayes (NB), k Nearest Neighbour (k-NN) and C4.5 on the Wisconsin breast cancer datasets. They compared efficiency and effectiveness of these algorithms in terms of accuracy, precision, sensitivity and specificity and achieved 97.13% accuracy and concluded that SVM achieved best performance in terms of precision and low error rate.

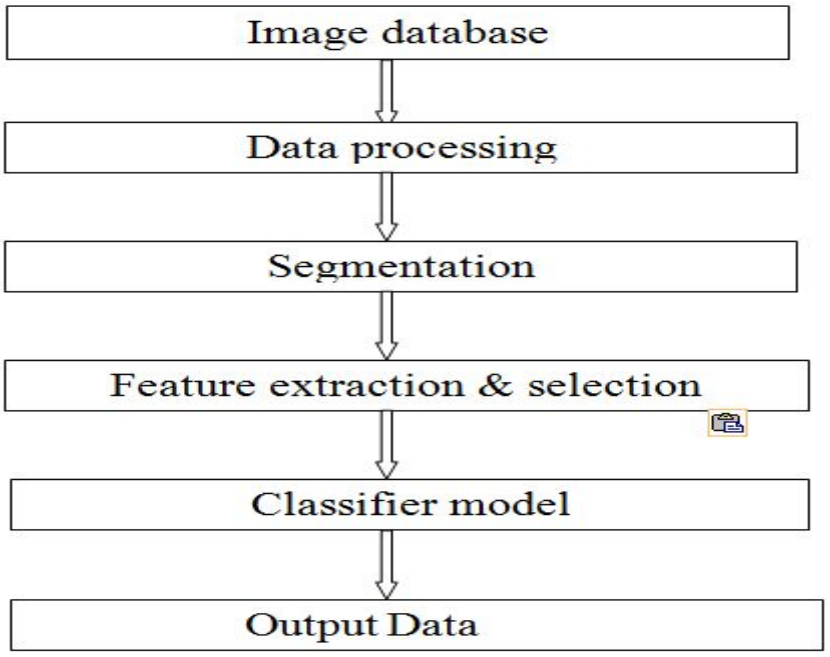
12. **Zhang Y D et al. (2016)** proposed a new approach for computer aided diagnosis of abnormal breast in mammogram images using the combination of three components weighted-type fractional fourier transform (WFRFT), principal component analysis (PCA) and support vector machine (SVM). For removing the redundant complexity ROI are identified. By combining SVM and principal component analysis they obtained sensitivity of 92.22% +_ 4.16%, specificity of 92.10% +_ 2.75% and accuracy of 92.16% +_ 3.60%.
13. **Pritom A I et al. (2016)** applied Naïve bayes, C4.5 decision tree and support vector machine classification algorithms and calculated their prediction accuracy on a medium sized dataset which contained 35 attributes and 198 cancer patient data. They classified the output instances attributes as "R" & "N" for recursive cancer and non-recursive cancer respectively. Results have shown that SVM has higher prediction accuracy i.e. 75.75% than Naïve Bayes 67.17% and C4.5 73.73%.
14. **Albayrak A et al. (2016)** proposed automated mitosis detection on histopathological images using convolutional neural networks. For identification of cellular structure cluster based segmentation is used. The segmented images are analyzed using Blob analysis. The overall accuracy is increased from 0,73 to 0,96 after dimension reduction by the combination of PCA+LDA methods (principal component analysis and Fischer's linear discriminant analysis). The precision, recall and F-measure values are 0.972, 0.66 and 0.786 respectively before dimension reduction step and after proposed dimension reduction strategy the values increased to 1, 0.94 and 0.969.
15. **Chen Y et al. (2016)** proposed a new computer aided diagnosis approach including biclustering and BP neural network algorithm to analyze breast tumors based on breast imaging reporting and data system (BI-RADS). Some BI-RADS lexicon based features were selected to explain the attributes of breast cancer, then each feature was given a score for the dataset. Biclustering technology is then used to determine local rules of diagnosis from large scale feature rating matrix. Training data is then processed using these important rules. BP network algorithm is implemented as an proficient classifier for diagnosis of benign and malignant breast tumors. They achieved accuracy, sensitivity, specificity as 96.1%, 96.7%,95.7% respectively.
16. **Burling-Claridge F et al. (2016)** investigated whether genetic programming (GP) and learning classifier systems (LCS) can perform well enough to classify mammographic images according to density levels as compared with conventional classification methods e.g. naïve Bayes, decision tree, K-nearest neighbor and support vector machines. They obtained 67.07 +_ 0.73% and 67.61 +_ 0.83% accuracy on MIAS and Inbreast image data

sets using Bayesian method and statistical feature and 62.86 +_ 0.70% and 51.99 +-1.28% accuracy using Local binary patterns (LBP).

17. **Jalalian A et al. (2017)** developed a novel computer-assisted diagnostic (CAD) framework for detecting breast cancer in computed tomography laser mammography (CTLM) images. It consists of three components namely segmentation volume of interests, development of dissociation model to disjoint VOIs into sub-VOIs as pre-step of feature extraction and detection and classification of the abnormality. They obtained classifier Accuracy, sensitivity and specificity as 95.20%, 92.40% and 98.00% respectively.
18. **Jiang F et al. (2017)** explored the techniques of transfer learning to tackle breast mass classification in mammographic images based on small-scale or limited image samples. Image processing is applied to enhance tissue characteristics of Region of interest (ROI) in the image. ROIs are first extracted (Otsu algorithm), refined and then data augmentation is applied. The obtained area under the receiver operating characteristic curves (AUC) was 0.88 and when the system learned from scratch the best receiver operating characteristics (ROC) is 0.82
19. **Xu B et al. (2017)** proposed a deep selective attention approach which aims at selecting only the valuable regions within the original images for classification. They developed a decision network to decide which portion of the image needs to be cropped and whether the cropped patch is necessary for classification or not. The patches which are selected are then trained by the classification network, which in turn provides feedback to the decision network to update its selection policy. They reduced the training time by 50% and achieved approximately 98% accuracy.
20. **Geras K J et al (2018)** developed a novel deep convolutional network (DCN) that is able to handle multiple views of screening mammography and utilized large high-resolution images without downscaling. They referred to this as a multi-view deep convolutional network (MV-DCN). The relation of the accuracy with the database size and image size is investigated.
21. **Sun L et al. (2019)** proposed an effective algorithm based on CNN and multiple mammography views for breast mass classification. They developed an improved architecture based on CNN It utilizes two subnetworks to extract features from MLO (mediolateral oblique) and CC (craniocaudal) view of breast mass images. They integrated the MVCNN (Multi-view convolutional neural Subnetwork) & MDCNN (Multi dilated convolutional neural subnetwork) to extract features from multiple views of the breast mass images.

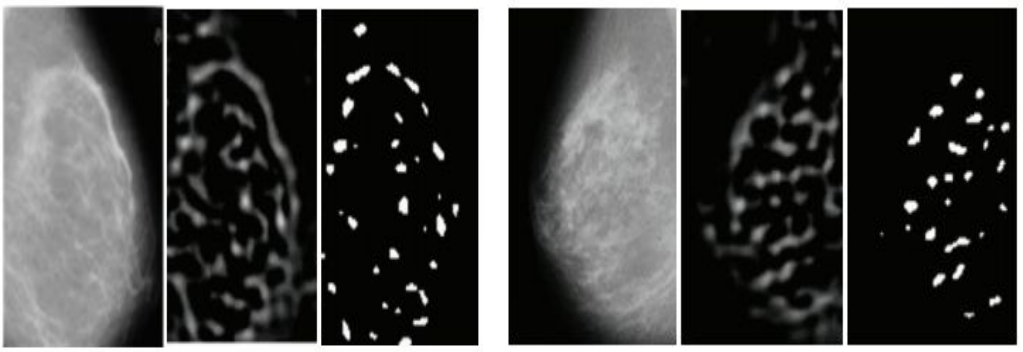
22. **Khan H N et al. (2019)** proposed a novel MVFFCADx (Multi-view feature fusion conventional computer-aided diagnosis) system which is based on the feature fusion strategy of four views of mammogram images, they analyzed the performance of augmentation on state-of-the-art CNN architecture through transfer learning between natural images and mammograms. They boosted the performance of mammograms classifications and decreased the computational complexity.
23. **Zheng J et al. (2020)** focused on combining machine learning with methods of features selection & extraction and evaluated their performance using classification and segmentation techniques. For breast cancer detection they built an ensemble classifier with an adaboost algorithm to diagnose the various metastases in breast tumors. Their experimental results have demonstrated accuracy level of 97.2%, sensitivity of 98.3% and specificity of 96.5%.
24. **Zhang X et al. (2020)** developed a linear discriminant analysis (LDA) with autoencoder neural networks using deep learning techniques to learn from the gene expression information. To assess the outcome of breast cancer an advanced ensemble classification has been developed based on deep learning. They achieved 98.27% accuracy.
25. **Wu N et al. (2020)** developed a two stage neural network for incorporating global and local information with appropriate training procedures. The network was trained and evaluated using 1,000,000 high resolution mammographic images. They identified different patterns which the network was not capable of capturing and error analysis was performed. They evaluated different methods of combining information from various mammographic images using a single neural network.

VIII. **Research methodology:**



- **Image database**: In this phase we will choose any one breast cancer database.
- **Data processing**: In this phase the noise will be removed from the image to decrease the execution time.
- **Segmentation**: In this phase the ROI's (region of interest) would be segmented.
- **Feature extraction & selection**: In this phase different feature extraction and selection methods would be applied such as texture, structural etc.
- **Classifier model**: In this phase XGBoost classifier model and a k-stage Resnet network would be used for training and testing purpose.
- **Output Data**: In this phase the final obtained images would be analyzed whether they are benign or malignant.

- **Hypotheses to be tested:**



(e) **(f)**

The expected outcome of this research is to first collect the breast cancer images, preprocess them to decrease the noise, separate regions of interest (ROIs) using segmentation, extract the image based on some feature, classify them using a classifier model, identify the target object and then diagnose whether it is benign or malignant image.

- **Sources of Information:**

  The publically available datasets such as DDSM, CBIS-DDSM, and the Digital breast tomosynthesis will be used.

- **Tools and Techniques of Research:**
  1. Resnet
  2. Deep neural network
  3. Python
  4. Tensor flow

- **Plan of work:**

Plan Of Work

Serial No.	TASK TITLE	START DATE	DUE DATE	DURATION	% OF TASK COMPLETE	Synopsis Presentation	Data collection, Pre-processing of Data	Segmentation, One research paper	Feature extraction & selection, one research paper	Classifier model identification,training and testing, one research paper	Result analysis, Thesis writing, Thesis submission
						Semester I	Semester II	Semester III	Semester IV	Semester V	Semester VI
						Jan-July 2020	July-Dec 2020	Jan-July 2021	July-Dec 2021	Jan-July 2022	July-Dec 2022
1	Synopsis Presentation										
1.1	Semester I	1/1/20	6/30/20	179	100%						
2	Data collection, Pre-processing of Data										
2.1	Semester II	7/1/20	12/31/20	180	22%						
3	Segmentation, One research paper										
3.1	Semester III	1/1/21	6/30/21	179	0%						
4	Feature extraction & selection, one research paper										
4.1	Semester IV	7/1/21	12/31/21	180	0%						
5	Classifier model identification,training and testing, one research paper										
5.1	Semester V	1/1/22	6/30/22	179	0%						
6	Result analysis, Thesis writing, Thesis submission										
6.1	Semester VI	7/1/22	12/31/22	180	0%						

IX. Expected outcome of research:

The expected outcome of research is early diagnosis of breast cancer with higher efficiency.

X. Tentative Chapterization

Chapter 1: Introduction of Research

Chapter 2: Literature Review

Chapter 3: Methodologies and Implementation

Chapter 4: Result and discussion

Chapter 5: Conclusion and Future work

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Date: 18/08/2020

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- https://en.wikipedia.org/wiki/Residual_neural_network

Document Information

Analyzed document	Rev Fival.doc (D82391548)
Submitted	10/22/2020 12:06:00 PM
Submitted by	Dr Pradeep Laxkar
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W	URL: https://www.researchgate.net/publication/322164442_Involvement_of_Machine_Learning ... Fetched: 12/29/2019 5:17:31 PM	1